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# Reducing clinical workload in the care prescription process: Optimization of order sets

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Order sets are a critical component in hospital information systems, designed to substantially reduce clinician workload and improve patient safety and health outcomes. Order sets represent clusters of order items, such as medications prescribed at hospital admission, that are administered to patients during their hospital stay. In prior research, we constructed order sets for defined time intervals during inpatient stay based on historical data on items ordered by clinicians across a large number of patients. In this study, we build on our prior work to formulate a mathematical program for optimizing order sets that are applicable across the entire duration of inpatient stay and are independent of the time intervals. Furthermore, due to the intractability of the problem, we develop a Greedy algorithm to tackle real-world test instances. We extract data sets for three clinical scenarios and conduct both cognitive and physical workload analyses. Finally, we extend a software application to facilitate the comparison of order sets by practitioners. Our computational results reveal that the optimization-based physical and cognitive workload models can solve small test instances to optimality. However, for real-world instances, the Greedy heuristic is more competitive, in particular when physical workload instead of cognitive workload is the optimization objective. Overall, the Greedy heuristic can solve the test instances within one minute and outperforms the mathematical program in 2/3 of the test instances within a time limit of ten minutes, demonstrating a feasible and promising approach to develop inpatient order sets that can subsequently be validated by clinical experts.

*Keywords*: Healthcare Information Systems; Health Informatics/Health Information Systems/Medical IS; Analytical Modeling; Heuristics

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## 1. Introduction

In healthcare information systems, Computerized Physician Order Entry (CPOE) has proven to be effective in increasing patient safety, reduce medication errors and costs (Nuckols et al. (2014)). Specifically, order sets support clinicians in high risk situations by serving as expert-recommended guidelines, reducing prescribing time by making complex ordering easier, increasing physician compliance with the current best practice and playing a vital role in reducing excessive ordering (Goldszer et al. (2017)). A characteristic of order sets is that specific orders can be predetermined to be “pre-set” or “defaulted-on” whenever the order set is used while others are “optional” or “defaulted-off” (though there is typically the option is to “deselect” defaulted-on orders in a given situation), see Olson et al. (2015). For instance, the ‘Asthma Admission Order Set’ shown in Figure 1 groups together order items for Asthma patients upon admission.

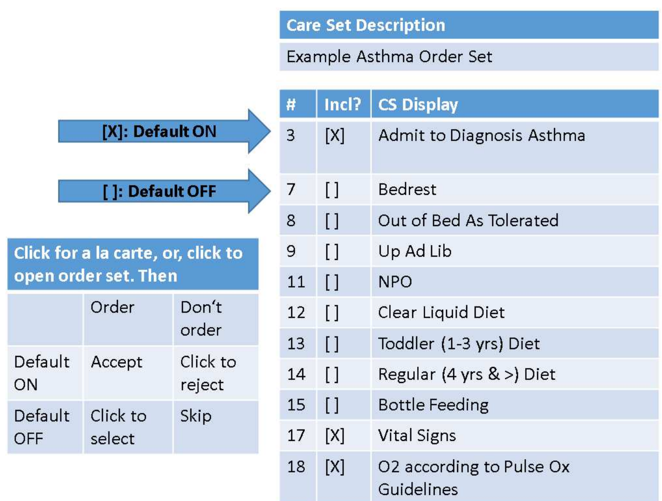


FIG. 1: Asthma admission order set Gartner et al. (2017)

The figure shows that order item number 3 – “Admit to Diagnosis Asthma” is defaulted ON while order item number 7 – “Bedrest” is defaulted off in the example asthma order set. In general, order items in order sets can be defaulted ON or OFF according to clinical relevance and frequency of use. An order item can be part of multiple order sets. Despite the benefits of order sets, historical data indicate a tremendous variability in order set usage by clinicians, driven largely by the diversity in patient population, physician experience, and system usability. Within CPOE, clinicians can search for particular orders by typing the order names and the search result includes all a la carte orders and order sets that match the keyword because order set usage is not mandatory. A la carte orders are individual orders that clinicians choose to enter without using order sets. Intuitively, ordering a la carte items takes more time compared to order sets because they have to be searched for and entered one by one. Some orders are standalone items and a la carte is the only way to prescribe them. Yet, reasons for ordering a la carte items instead of order set items come from a physician’s disagreement with order set content, unfamiliarity with order sets, inconsistency of order set content with current best practices, and at times, a simple need for only one or two orders. Ordering efficiency decreases when order sets contain items that do not match the workflow or the patient's condition, forcing clinicians to go through long lists of orders to determine each item's relevance to particular patients, and eventually rely on a la carte orders which are time-consuming and subject to errors (Zhang et al. (2014)). Size of order sets is at least 2, varying depending on their purpose.

This paper aims to address these challenges by proposing and testing approaches based on Discrete and Metaheuristic Optimization to create order sets from usage data with the objective of minimizing clinicians' workload. Clinicians' workload can be measured in two ways: Physical workload (PW) associated with mouse clicks and cognitive workload (CW) associated with mental tasks in order prescription. PW is associated with i) assigning patients' orders to order sets, ii) deselecting non-required order items from order sets, iii) deselecting order items which are prescribed multiple times and iv) ordering items a la carte. In addition, CW is incurred when order items are confirmed to be defaulted ON or OFF after assigning order sets to patients.

In this paper, we build on previous work from Gartner et al. (2017) who developed a time-dependent mathematical program to generate order sets, assign patients' order items to order sets or, if workload cannot be minimized by using order sets, items are selected individually. Figure 2 illustrates the notion of time-dependent vs. -independent order set optimization. In the case of time-dependent order set optimization, time intervals are explicit. For example, assume we have 3 time intervals ($t = 0, 1, 2$) that distinguish different episodes of the patients' length of stay. Interval $t = 0$ represents the time interval 24 hours before admission until admission, $t = 1$ represents the admission and $t = 2$ represents the patient's treatment stage. Witin these time intervals, order items can be grouped into, for example, pre-admission order sets for $t = 0$. Admission-related order items are grouped in admission order sets ($t = 1$) and treatment-related items are clustered into treatment order sets for $t = 2$. On the contrary, with time-independent order set optimization, all items that are relevant for prescription during the entire patients' hospital visit are grouped into time-independent order sets which include pre-admission, admission and treatment stage orders.

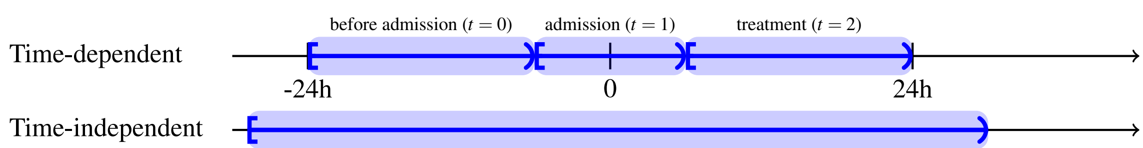


FIG. 2: Time-dependent vs. time-independent order set optimization

To address the time-independent order set optimization problem, we extend the model from Gartner et al. (2017) in the following four ways: Firstly, we formulate a mathematical program for time-independent order sets. Because the problem is intractable, we secondly develop a Greedy algorithm to tackle real-world test instances. Thirdly, we solve real-world data sets using three types of clinical conditions and conduct a cognitive and physical workload analysis. Finally, we extend the graphical user interface to facilitate the comparison of order sets by practitioners.

The remainder of this paper is structured as follows. In the next section, we provide an overview of related work. Next, we provide a formal description of the problem and the mathematical programming formulation followed by a description of the heuristic solution approach. In a computational study, we demonstrate the effectiveness of our approach based on data from a major hospital in the United States. In that section, we describe our evaluation metrics followed by a presentation of our results. We finally summarize our paper with a conclusion and outline streams for further research.

## 2. Related Work

We focus on two relevant fields: Order set management and medical item clustering.

### 2.1 *Order Set Management*

Table 1 provides an overview of order set management problems.

Table 1: Overview of order set management problems (CW: Cognitive Workload, PW: Physical Workload)

| Publication | Zhang et al. (2014) | Zhang and Padman (2015) | Gartner et al. (2015) | Gartner et al. (2017) | Our paper |
|---|---|---|---|---|---|
| Objective function | CW, PW | CW | PW | CW | CW, PW |
| Problem size | large | large | small | large | small, large |
| Method | 2 stage heuristic optimization embedding $K-$means clustering | Tabu-search optimization | Mathematical Programming, $K-$means decomposition | Mathematical Programming, $K-$means decomposition | Mathematical Programming, Greedy Heuristic |
| Time dimension | yes (flexible) | yes (flexible) | yes (fixed) | yes (fixed) | no |
| Clinical Condition | acute, chronic, surgical | acute | acute | chronic | acute, chronic, surgical |

Related work on order set management includes Zhang et al. (2014) and the references therein. The authors employ heuristic methods to reduce physician workload in hospitals through order set improvement. Gartner et al. (2015) provide a mathematical model and solve the order set optimization problem with fixed time intervals to optimality with the objective to reduce physician workload for one clinical condition. Time intervals were fixed because the use case in reality is that clinicians should be able to prescribe, for example, admission order sets to patients. Those contain prescriptions and activities carried out to admit the patient to the hospital. On an aggregated view, time-independent order sets allow to bundle all order items required during the patients' entire hospital stay.

Our study has a similar focus as compared to Zhang et al. (2014)'s, Zhang and Padman (2015)'s, Gartner et al. (2015)'s and Gartner et al. (2017)'s studies. The extension, however, is that we provide a mathematical model without decomposing it into fixed time intervals. Because of the larger number of order items, the problem is expected to be computationally more challenging because of the union of all order items in all time intervals. Another extension is that we develop a Greedy heuristic which determines order sets based on frequency measures in the item demand. Finally, we focus on cognitive workload in addition to physical workload and two additional clinical conditions.

Chen et al. (2017) evaluate the accuracy of predicting order patterns for patients. They use probabilistic topic models to generate clinical topic models and to predict subsequent clinical orders. Using classification accuracy as performance metric, the authors demonstrate that probabilistic topic modelling can increase classification accuracy as compared to using existing order sets as a classifier. Their approach is different to our approach since they create a set of clinical topics whereas we create data-driven order sets.

### 2.2 *Clustering Medical Items*

Focusing on healthcare, Cardoen et al. (2015) has similarities to our work because they group medical items for surgeries which can be seen as a clustering problem. The difference to our problem is, among others, that we have a defaulted ON and defaulted OFF option as shown in Figure 1. Each order item in an order set can be defaulted ON or OFF according to clinical relevance and frequency of use (Gartner et al. (2017)) With respect to the solution methodology, we use a different heuristic approach. Similarly, Dobson et al. (2015) propose a mathematical programming formulation to decide on the composition of instrument trays to minimize the costs of owning, maintaining, and using both the trays and the instruments.

As a conclusion of our literature review, our study can be considered to be the first to employ mathematical programming for the time-independent order set optimization problem. In addition, we develop an exact and a heuristic approach to solve real-world test instances. Furthermore, we prove structural properties of the problem. Finally, we develop a Java-based application with a graphical user interface that covers all components: order set optimization and current order set usage. This allows clinicians to take advantage of the methods we develop in this paper.

## 3. Problem Description, Model Formulation and Complexity

In what follows, we provide a concise problem description followed by the mathematical model that clusters order items to which patients are assigned. We then provide insights into the complexity of the problem. In the remainder of this paper, we will use the following terms as synonyms: activities, items, orders, order items, procedures and treatments. Similarly, clusters and order sets are used synonymously.

### 3.1 *Problem Description*

When patients are admitted to the hospital, we wish to assign these patients to clusters which represent sets of order items. Unlike a la carte order placement, where clinicians need to apply one mouse click every time to select an individual order, defaulted ON items are automatically selected when an order set is chosen. With additional clicks, users can add defaulted OFF items to the selection or deselect defaulted ON items from the order placement, see Figure 1 in Section 1.

In what follows, we start with the definition of the general parameters for building clusters and then turn to patient-related parameters as well as workload parameters for the assignment of patients' order items to order sets, and for selecting order items a la carte, among others.

3.1.1 *Clusters, Order Items, Patients and Patients' Order Items.* Order sets are indexed using the set $\mathscr{K} := \{1,2,\dots,K\}$ with the maximum number of order sets denoted by $K$. Order item demand, which is the universe of order items required by all patients, is denoted by set $\mathscr{I} := \{1,2,\dots,I\}$. In this set, $I$ is the biggest index of order items. Patients are denoted by set $\mathscr{P} := \{1,2,\dots,P\}$ in which $P$ is the last index of all patients. Let $\mathscr{I}_p$ denote patient $p$'s order items.

3.1.2 *Workload.* We break down the clinicians' workload into i) selection workload when patients are assigned to order sets, ii) workload associated with the selection and de-selection of patients' order items from order sets, and iii) workload associated with the confirmation of patients' order items.

Order set selection workload. When an order set is assigned to a patient, we denote the workload associated with each selection as $c^{\text{os}}$.

Selection workload for required order items. If additional order items are required (in addition to the activities in an order set), workload of $c^{\text{off,on}}$ arises for each additional order item. Selection workload for adding an a la carte item is denoted by $c^{\text{alc}}$. We denote a la carte workload as $c^{\text{alc}}$ and assume that the workload is greater than or equal to zero.

Deselection workload for non-required and multiple prescribed order items. When an order item that is part of an order set must be deselected for that particular patient because it is not required, there is a workload which we denote by $c^{\text{off,non-req}}$. Sometimes, patients may be assigned to multiple order sets. In that case, it can happen that order items are prescribed multiple times and workload associated with the deselection of items that are prescribed multiple times are denoted by $c^{\text{off,mult}}$.

Cognitive workload. We denote $c^{\text{conf,on}}$ as cognitive workload when a patient's order item is confirmed as defaulted ON in an order set. Similarly, we denote $c^{\text{conf,off}}$ as cognitive workload when an order item is confirmed as defaulted OFF in an order set. As a consequence, it is not assigned to the patient.

### 3.2 *Model Formulation*

We will now introduce the decision variables, the objective function and the constraints to model the problem. The decision variables are shown in Table 2.
We denote the $a^{\text{off}}_{i,k}$ and $a^{\text{on}}_{i,k}$ variables as 'clustering variables' because in each order set $k$ (cluster) they will provide information about which order item is defaulted OFF and ON, respectively. All other variables will mainly be used for assigning patients to order sets or performing decisions on the patients' item level to determine the physician workload in our objective function. With the introduced parameters and decision variables, our mathematical model can be formulated as a Mixed-Integer Program (MIP) follows:

$$
\begin{aligned}
\text{minimize}\quad z = \sum_{p\in\mathscr{P}} \Bigg[ & \sum_{i\in\mathscr{I}_p} c^{\text{alc}} \cdot x^{\text{alc}}_{p,i} + \sum_{k\in\mathscr{K}} c^{\text{os}} \cdot x^{\text{os}}_{p,k} \\
& + c^{\text{off,non-req}} \cdot \left( \sum_{i\in\mathscr{I}: i\notin\mathscr{I}_p} \sum_{k\in\mathscr{K}} x^{\text{on,off}}_{p,i,k} + c^{\text{off,mult}} \cdot \sum_{i\in\mathscr{I}} x^{\text{m,on}}_{p,i} \right) \\
& + c^{\text{off,on}} \cdot \sum_{i\in\mathscr{I}_p} \sum_{k\in\mathscr{K}} x^{\text{off,on}}_{p,i,k} + \sum_{i\in\mathscr{I}_p} \sum_{k\in\mathscr{K}} c^{\text{conf,on}} \cdot x^{\text{conf,on}}_{p,i,k} + \sum_{i\in\mathscr{I}: i\notin\mathscr{I}_p} \sum_{k\in\mathscr{K}} c^{\text{conf,off}} \cdot x^{\text{conf,off}}_{p,i,k} \Bigg]
\end{aligned}
\tag{3.1}
$$

subject to

Table 2: Overview of decision variables

| Decision variable | Description |
|---|---|
| $a_{i,k}^{\text{off}}$ | 1, if order item $i$ is defaulted OFF in order set $k$, 0 otherwise |
| $a_{i,k}^{\text{on}}$ | 1, if order item $i$ is defaulted ON in order set $k$, 0 otherwise |
| $x_{p,i}^{\text{alc}}$ | 1, if patient $p$'s order item $i$ is chosen from a la carte items, 0 otherwise |
| $x_{p,i,k}^{\text{conf,off}}$ | 1, if patient $p$'s order item $i$ chosen from order set $k$ is confirmed OFF, 0 otherwise |
| $x_{p,i,k}^{\text{conf,on}}$ | 1, if patient $p$'s order item $i$ chosen from order set $k$ is confirmed ON, 0 otherwise |
| $x_{p,i,k}^{\text{off,on}}$ | 1, if patient $p$'s order item $i$ is defaulted OFF in order set $k$ and is selected, 0 otherwise |
| $x_{p,i,k}^{\text{on,off}}$ | 1, if patient $p$'s order item $i$ is defaulted ON in order set $k$ and is deselected, 0 otherwise |
| $x_{p,k}^{\text{os}}$ | 1, if patient $p$ is assigned to order set $k$, 0 otherwise |
| $x_{p,i,k}^{\text{os,on}}$ | 1, if patient $p$ is assigned to order set $k$ and order $i$ of that patient is defaulted ON, 0 otherwise |
| $x_{p,i}^{\text{m,on}}$ | an integer number which represents how often patient $p$'s order item $i$ has to be deselected because it is prescribed in order sets multiple times |

$$x_{p,i}^{\text{alc}} + \sum_{k\in\mathscr{K}} \left(x_{p,i,k}^{\text{conf,on}} + x_{p,i,k}^{\text{off,on}}\right) = 1 \qquad \forall p \in \mathscr{P}, i \in \mathscr{I}_p \tag{3.2}$$

$$x_{p,k}^{\text{os}} + a_{i,k}^{\text{on}} - x_{p,i,k}^{\text{on,off}} \leqslant 1 \qquad \forall p \in \mathscr{P}, k \in \mathscr{K}, i \in \mathscr{I} : i \notin \mathscr{I}_p \tag{3.3}$$

$$x_{p,k}^{\text{os}} + a_{i,k}^{\text{off}} - x_{p,i,k}^{\text{conf,off}} \leqslant 1 \qquad \forall p \in \mathscr{P}, k \in \mathscr{K}, i \in \mathscr{I} : i \notin \mathscr{I}_p \tag{3.4}$$

$$a_{i,k}^{\text{off}} - x_{p,i,k}^{\text{off,on}} \geqslant 0 \qquad \forall p \in \mathscr{P}, k \in \mathscr{K}, i \in \mathscr{I}_p \tag{3.5}$$

$$a_{i,k}^{\text{on}} - x_{p,i,k}^{\text{on,off}} \geqslant 0 \qquad \forall p \in \mathscr{P}, k \in \mathscr{K}, i \in \mathscr{I} : i \notin \mathscr{I}_p \tag{3.6}$$

$$x_{p,i,k}^{\text{os,on}} \geqslant x_{p,k}^{\text{os}} + a_{i,k}^{\text{on}} - 1 \qquad \forall p \in \mathscr{P}, k \in \mathscr{K}, i \in \mathscr{I}_p \tag{3.7}$$

$$x_{p,i}^{\text{m,on}} \geqslant \sum_{k\in\mathscr{K}} x_{p,i,k}^{\text{os,on}} - 1 \qquad \forall p \in \mathscr{P}, i \in \mathscr{I}_p \tag{3.8}$$

$$a_{i,k}^{\text{on}} - x_{p,i,k}^{\text{conf,on}} \geqslant 0 \qquad \forall p \in \mathscr{P}, k \in \mathscr{K}, i \in \mathscr{I}_p \tag{3.9}$$

$$a_{i,k}^{\text{off}} - x_{p,i,k}^{\text{conf,off}} \geqslant 0 \qquad \forall p \in \mathscr{P}, k \in \mathscr{K}, i \in \mathscr{I} : i \notin \mathscr{I}_p \tag{3.10}$$

$$a_{i,k}^{\text{on}} + a_{i,k}^{\text{off}} \leqslant 1 \qquad \forall i \in \mathscr{I}, k \in \mathscr{K} \tag{3.11}$$

$$x_{p,k}^{\text{os}} - x_{p,i,k}^{\text{off,on}} \geqslant 0 \qquad \forall p \in \mathscr{P}, i \in \mathscr{I}_p, k \in \mathscr{K} \tag{3.12}$$

$$x_{p,k}^{\text{os}} - x_{p,i,k}^{\text{conf,on}} \geqslant 0 \qquad \forall p \in \mathscr{P}, i \in \mathscr{I}_p, k \in \mathscr{K} \tag{3.13}$$

$$x_{p,k}^{\text{os}} - x_{p,i,k}^{\text{on,off}} \geqslant 0 \qquad \forall p \in \mathscr{P}, i \in \mathscr{I} : i \notin \mathscr{I}_p, k \in \mathscr{K} \tag{3.14}$$

$$x^{\text{os}}_{p,k} - x^{\text{conf,off}}_{p,i,k} \geqslant 0 \qquad \forall p \in \mathscr{P}, i \in \mathscr{I} : i \notin \mathscr{I}_p, k \in \mathscr{K} \tag{3.15}$$

$$a^{\text{on}}_{i,k}, a^{\text{off}}_{i,k} \in \{0,1\} \qquad \forall i \in \mathscr{I}, k \in \mathscr{K} \tag{3.16}$$

$$x^{\text{os}}_{p,k} \in \{0,1\} \qquad \forall p \in \mathscr{P}, k \in \mathscr{K} \tag{3.17}$$

$$x^{\text{alc}}_{p,i} \in \{0,1\} \qquad \forall p \in \mathscr{P}, i \in \mathscr{I}_p \tag{3.18}$$

$$x^{\text{conf,off}}_{p,i,k}, x^{\text{on,off}}_{p,i,k} \in \{0,1\} \qquad \forall p \in \mathscr{P}, i \in \mathscr{I} : i \notin \mathscr{I}_p, k \in \mathscr{K} \tag{3.19}$$

$$x^{\text{conf,on}}_{p,i,k}, x^{\text{os,on}}_{p,i,k}, x^{\text{off,on}}_{p,i,k} \in \{0,1\} \qquad \forall p \in \mathscr{P}, i \in \mathscr{I}_p, k \in \mathscr{K} \tag{3.20}$$

$$x^{\text{m,on}}_{p,i} \in \mathbb{N}_{\geqslant 0} \qquad \forall p \in \mathscr{P}, i \in \mathscr{I}_p \tag{3.21}$$

Objective function (3.1) minimizes workload for selecting patients' order items from a la carte, assigning patients to order sets, deselecting defaulted ON order items from order sets, selecting defaulted OFF order items from order sets, confirm defaulted ON order items within order sets and confirm defaulted OFF order items within order sets. We will denote the different terms of the objective function as $z^{\text{alc}}$, $z^{\text{os}}$, $z^{\text{off,non-req}}$, $z^{\text{off,mult}}$, $z^{\text{off,on}}$, $z^{\text{conf,on}}$ and $z^{\text{conf,off}}$. Constraints (3.2) ensure that each patient's required order item is either selected a la carte or it is selected from order sets. If it is selected from order sets, the order item is confirmed defaulted ON or it is switched on because it is defaulted OFF. Constraints (3.3) ensure that if a patient is assigned to an order set and a non-required order item is defaulted ON, then it has to be de-selected. Constraints (3.4) ensure that if a patient is assigned to an order set and a non-required order item is defaulted OFF, then it has to be confirmed to be OFF. Constraints (3.5) ensure that if a patient's order item is switched ON from defaulted OFF, it has to be defaulted OFF in the corresponding order set. Constraints (3.6) ensure that if a patient's non-required order item is switched OFF from defaulted ON, it has to be defaulted ON in the corresponding order set. Constraints (3.7) ensure that if the patient is assigned to an order set and the order item is defaulted ON, the $x^{os,on}_{h,p,i,k}$-variables have to be 1. Using these variables, Constraints (3.8) ensure that if the patient's required order item is selected multiple times, it has to be counted by the auxiliary decision variables. Constraints (3.9) ensure that a patient's required order item can only be confirmed on if it is defaulted ON in the corresponding order set. Constraints (3.10) ensure that a patient's required order item can only be confirmed OFF if it is defaulted OFF in the corresponding order set. Constraints (3.11) ensure that an order item cannot be defaulted ON and defaulted OFF in the same order set at the same time interval. Constraints (3.12) ensure that if a patient's order item is switched on from defaulted OFF in an order set, the patient has to be assigned to the corresponding order set. Constraints (3.13) ensure that if a patient's order item is switched OFF from defaulted ON in an order set, the patient has to be assigned to the corresponding order set. Constraints (3.14) ensure that if a patient's defaulted ON order item is switched OFF, the patient has to be assigned to the corresponding order set. Constraints (3.15) ensure that if a patient's defaulted OFF order item is confirmed OFF, the patient has to be assigned to the corresponding order set. (3.16)–(3.20) are the decision variables and their domain.

The parameters introduced in the problem description are similar to the ones introduced in Gartner et al. (2017) and Gartner et al. (2015). The problem and model formulation is, however, different to the one developed by Gartner et al. (2017) because of the time-independence of order sets that are now generated. The time index is removed which means that the problem does not decompose into disjoint time intervals. As a consequence, the temporal decomposition strategy introduced in Gartner et al. (2015) for the MCC problem cannot be employed any more. As a consequence, a significantly larger number of order items are expected to be part of the solution space for the $a-$variables and most of the $x-$variables.

### 3.3 *Complexity*

Proposition The physical workload minimizing Order Set Optimization Problem with $c^{\text{os}} = 1, c^{\text{alc}} = 1, c^{\text{off,mult}} = 1, c^{\text{off,on}} = 1, c^{\text{off,non-req}} = 1, c^{\text{conf,on}} = 0, c^{\text{conf,off}} = 0$, $K = 1$ and $P > 1$ is NP-Hard.

The optimization problem reduces to the set covering problem (Garey and Johnson (1979)). The optimal item combination in order set $K = 1$ and patients' order set and a la carte assignment has to be found such that mouse clicks are minimized. Figure 3 shows different combinations of sets covered by using $|\mathscr{I}| = 3$ order items.

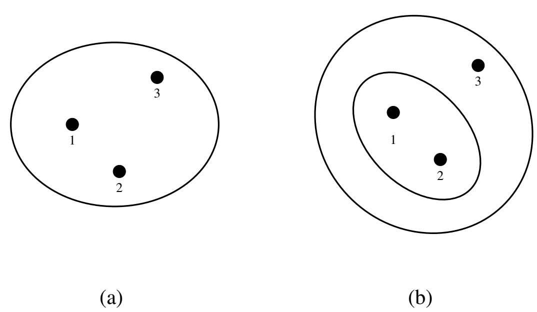


FIG. 3: All order items a la carte (a) and the set of a la carte items plus one order set consisting of items $\mathscr{I} := \{1,2\}$ (b)

Since the problem can be intractable already for small sizes of the order set optimization problem, a promising way to solve it is a Greedy-based heuristic which will be introduced next.

## 4. A Greedy-based Decomposition Heuristic

Instead of solving the entire model (3.1)–(3.20), we use a decomposition approach which breaks the problem into a clustering and an assignment problem. More specifically, we determine the value of the clustering variables $a^{\text{on}}_{i,k}$ heuristically. We introduce a threshold parameter $\kappa$ and relative frequency measure $\xi_{i,k}$ which is the relative frequency of item $i$ when splitting the patient demand into subsets $k = 1,\ldots,K$. The threshold parameter $\kappa$ can be determined by parameter optimization or set manually. For example if $\kappa = 0.5$, then order items which were prescribed in 50% of the cases in subset $k$ of the patients will be defaulted-on in the corresponding order set. The $x$-variables which determine whether patients' order items are chosen from order sets or a la carte are determined using our MIP.

Algorithm 4.1 shows the pseudocode of our Greedy heuristic.

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Algorithm 4.1: Greedy-based decomposition heuristic

1: Split $\mathscr{P}$ into $K$ disjoint subsets $\mathscr{P}_1, \mathscr{P}_2, \ldots, \mathscr{P}_K$.
2: **for all** $k \in \mathscr{K}$ **do**
3: Let $\xi_{i,k}$ denote the relative frequency of order items $\mathscr{I}_p$ for patient $p \in \mathscr{P}_k$
4: **if** $\xi_{i,k} \geqslant \kappa$ **then**
5: Fix defaulted-on variables $a^{\text{on}}_{i,k} = 1$
6: **else**
7: Fix defaulted-on variables $a^{\text{on}}_{i,k} = 0$
8: **end if**
9: **end for**
10: Solve model (3.1)–(3.21) based on fixed clusters.

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In Line 1 we split the set of patients into $k$ $(1 \leqslant k \leqslant K)$ groups and calculate the relative frequency $\xi_{i,k}$ of each order item $i$ in group $k$. Afterwards, we fix the defaulted-on variables in the order sets in Line 7 if threshold $\kappa$ is exceeded for the relative frequency of the occurrence of each item. In our experimental analysis, we set $\kappa = 0.5$ which we determined using parameter optimization for a small set of acute care test instances, see Figure 4.

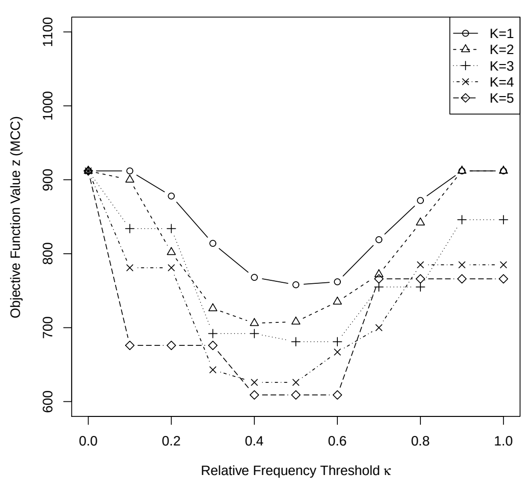


FIG. 4: Parameter optimization results

A demonstration that our Greedy heuristic fails optimality will be shown next.

Proposition The Greedy heuristic fails to guarantee optimality.

*Proof.* *Proof by reductio ad absurdum* Let $\mathscr{I} = \{1,2,3,4\}$ be the set of order items, $\mathscr{P} = \{1,2\}$ patients, $\mathscr{I}_1 = \{1,2,3,4\}$ and $\mathscr{I}_2 = \{1\}$ be the set of order items required by the patients. Since the Greedy heuristic decides on the majority of order items required by patients, it would create $\mathscr{A}^{\text{on}} = \{1\}$ as order set because the item is required by both patients. However, this solution is dominated by creating one order set based on all first patient's order items, assigning the first patient to the order set and selecting the second patient's order item from a la carte. $\square$

## 5. Experimental Analysis

In the following, we provide an experimental investigation of the presented methods. We first give a description of the data employed for our study, followed by an analysis of each of our approaches. Within each approach and test instance, computation times and workload are reported. For the MIP approach, the linear programming (LP) relaxation gap is provided.

### 5.1 *Data and General Parameters*

5.1.1 *Data.* We evaluated our approaches on data from a major U.S. university hospital and focused on the following clinical conditions with moderate severity: 'Bronchiolitis and pneumonia with respiratory syncytial virus', 'Asthma' and 'Tonsil and adenoid procedures' patients. We denote these conditions henceforth as 'acute care', 'chronic care' and 'surgical care' conditions, respectively. Our instances consist of patients to whom orders were prescribed between 24 hours before and after admission.

| Dataset | Clinical Condition | $\|\mathscr{P}\|$ | Unique orders | $\sum_{p\in\mathscr{P}} \|\mathscr{I}_p\|$ | PW | CW |
|---|---|---|---|---|---|---|
| Acute | Bronchiolitis and pneumonia with respiratory syncytial virus | 83 | 559 | 4,723 | 3,630 | 6,174.3 |
| Chronic | Asthma | 106 | 697 | 7,685 | 6,227 | 9,857.2 |
| Surgical | Tonsil and adenoid procedures | 79 | 627 | 5,111 | 3,752 | 6,149.6 |

Table 3: Summary statistics of the data

The table reveals that the instances consist of 83, 106 and 79 patients for the acute, chronic and surgical care condition, respectively. Moreover, 4,723, 7,685 and 5,111 order items were prescribed, respectively which means that an average between 56.9 and 72.5 order items were required by each of the patients. For the acute, chronic and surgical care patients 559, 697 and 627 unique order items were prescribed, respectively. In the current system, 39, 32 and 32 unique order sets were used for the acute, chronic and surgical care conditions, respectively, along with a la carte orders. The table also reveals that, for example, in the acute condition a physical workload (PW) of 3,630 clicks was required to prescribe all order items to patients. However, for surgical patients, a cognitive workload (CW) of 6,149.6 was required. Cost coefficients are discussed in the next subsection.

We joined usage data from the current CPOE system with data from the electronic medical record. In doing so, we obtained time stamps for the current order set assignments and patient demand, among others. This allows us to generate all parameters for our exact and heuristic approaches and to compare the solution with the clinicians' current workload.

All computations were performed on an Intel Core i7-4940MX CPU with 32 GB RAM running Windows 7 operating system. The models were coded in Java in an ILOG Concert environment. The solver used was IBM ILOG CPLEX 12.6 (64 bit).

5.1.2 *Evaluating the Frequency of Order Set Prescriptions.* Figure 5 provides an overview of order sets prescribed to patients in the current system.

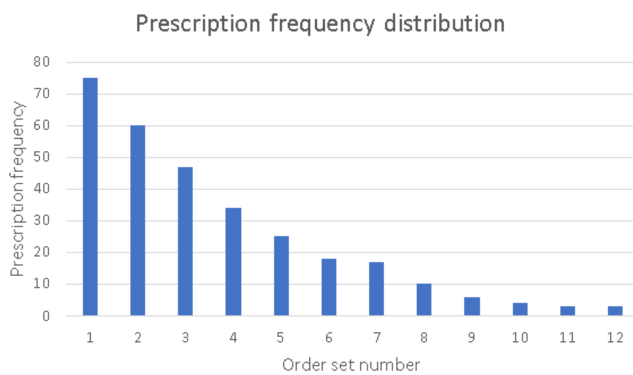


FIG. 5: Frequency distribution of order sets currently in use

The figure reveals that 10 order sets are most commonly used and may be prescribed multiple times to patients.

5.1.3 *General Parameters.* Table 4 shows how we chose the workload coefficients of the objective function. Measuring the clinicians' workload associated with their mouse clicks are framed as physical workload (PW). We also evaluate cognitive workload denoted by CW (Zhang et al. (2014)). The objective function coefficients are set according to the values shown in Table 4.

Table 4: Setup of our objective function coefficients (Zhang et al. (2014))

| Metric | $c^{\text{alc}}$ | $c^{\text{os}}$ | $c^{\text{off,non-req}}$ | $c^{\text{off,mult}}$ | $c^{\text{conf,on}}$ | $c^{\text{conf,off}}$ | $c^{\text{off,on}}$ |
|---|---|---|---|---|---|---|---|
| PW | 1.0 | 1.0 | 1.0 | 1.0 | 0.0 | 0.0 | 1.0 |
| CW | 1.1 | 1.1 | 1.3 | 1.3 | 1.0 | 1.1 | 1.4 |

The table shows that all CW coefficients are greater than or equal to one while using the PW metric, two workload coefficients are zero. Also, since $c^{\text{off,on}} \geqslant c^{\text{alc}}$, switching order items from default OFF to ON is dominated by a la carte assignment.

In what follows, we present the results of our mathematical model and the heuristic. We stop the computation of the MIP after 600s computation time. We report the relative gap between the best integer solution's objective function value and the objective function value found by solving the linear program (without integrality, refered to as LP relaxation gap).

### 5.2 *Computational Complexity and LP Relaxation Gap Analysis*

We break down our computational complexity analysis by the physical and cognitive workload minimization model. For each model, we report the results of the acute, chronic and surgical care condition.

The performance of the approaches for PW minimization is shown in Table 5.

Table 5: Computation time analysis results for the PW metric (Best performance figures are in bold. Figures marked with * are LP relaxation gaps obtained after approx. 600s.)

| Condition | $\lvert\mathscr{K}\rvert$ | MIP #Var. | MIP #Constr. | MIP Comp. time [s] | MIP $z$ | MIP Gap [%] | Greedy Heuristic Comp. time [s] | Greedy Heuristic $z$ | Greedy Heuristic Impr. [%] |
|---|---|---|---|---|---|---|---|---|---|
| acute | 1 | 61,208 | 148,637 | 600 | 3,931 | 21.77* | 0.077 | **3,764** | 4.25 |
| | 2 | 112,970 | 287,828 | 600 | 4,643 | 90.48* | 0.435 | **3,671** | 20.93 |
| | 5 | 268,256 | 705,401 | 600 | 4,723 | 98.24* | 2.015 | **3,541** | 25.03 |
| chronic | 1 | 97,740 | 237,016 | 600 | 5,634 | 19.52* | 0.115 | **5,259** | 6.67 |
| | 2 | 180,110 | 458,662 | 600 | 7,490 | 98.04* | 1.133 | **5,110** | 31.78 |
| | 5 | 427,220 | 1,123,600 | 601 | 7,685 | 98.62* | 1.605 | **4,893** | 36.33 |
| surgical | 1 | 65,572 | 158,821 | 600 | **3,597** | 9.16 * | 0.081 | 3,616 | -0.53 |
| | 2 | 120,922 | 307,420 | 600 | 4,979 | 93.50 * | 0.585 | **3,501** | 29.68 |
| | 5 | 286,972 | 753,217 | 600 | 5,111 | 98.45 * | 3.150 | **3,258** | 36.26 |

The figures reveal that none of the problem instances can be solved to optimality by the MIP approach. More specifically, the best LP relaxation gap is 9.16% for the surgical condition test instance. Another observation for the MIP approach is that the objective function value $z$ increases when $K$ increases. This is counter-intuitive but can be explained by the increased model complexity. When running small-scale instances to optimality (see Appendix A) $z$ decreases with increasing $K$. Another observation is that the Greedy approach outperforms the MIP approach in all but one problem instances. In the case of the chronic condition, the improvement when comparing the Greedy approach with the MIP approach is best. More specifically, for $K$=5, the Greedy approach improves the MIP by 36.33%. One explanation for this phenomenon is that the test instances for the chronic condition are largest with 106 patients. Accordingly, the problem sizes which are reported by the number of decision variables and constraints, are the largest for that condition. Overall, we can observe that the main driver for the problem size is the number of order sets $\lvert\mathscr{K}\rvert$ which dramatically increases and more than quadruples from $\lvert\mathscr{K}\rvert = 1$ to $\lvert\mathscr{K}\rvert = 5$.

The performance of the approaches for CW as minimization objective is shown in Table 6.
The figures show a similar pattern with respect to the objective function behavior in the MIP approach. Increasing the number of order sets $K$ may lead to even worse objective function values which is true for the data sets of the chronic and the surgical condition. For the acute condition, $z$ decreases when $K$ is set from 1 to 2. But then it increases again when $K = 5$. One explanation of this phenomenon is that the problem sizes are just too big to handle with the solver and it converges very slowly.

The figures also reveal that the difference between the Greedy approach and the MIP, which is used as a heuristic because it is not solved to optimality, is less than 1%. Another observation is that the LP relaxation gaps of the MIP are smaller when comparing the CW model with the PW model. A more detailed analysis of the CPLEX output revealed that the initial objective function value is already close to the LP relaxation gap. More specifically, in the initial solution the solver sets all order items a la

Table 6: Computation time analysis results for the CW metric (Best performance figures are in bold. Figures marked with * are LP relaxation gaps obtained after approx. 600s.)

| Condition | $\lvert\mathcal{K}\rvert$ | MIP #Var. | MIP #Constr. | MIP Comp. time [s] | MIP $z$ | MIP Gap [%] | Greedy Heuristic Comp. time [s] | Greedy Heuristic $z$ | Greedy Heuristic Impr. [%] |
|---|---|---|---|---|---|---|---|---|---|
| acute | 1 | 108,164 | 283,664 | 601 | **5,185.9** | 2.24* | 1.775 | 5,194.3 | -0.16 |
| | 2 | 206,882 | 557,882 | 601 | **5,181.5** | 7.07* | 5.546 | 5,192.5 | -0.21 |
| | 5 | 503,036 | 1,380,536 | 601 | 5,195.3 | 7.33* | 23.901 | **5,192.1** | 0.06 |
| chronic | 1 | 172,319 | 451,674 | 600 | **8,434.3** | 3.44* | 3.359 | 8,450.0 | -0.19 |
| | 2 | 329,268 | 887,978 | 601 | 8,453.5 | 7.71* | 9.801 | **8,450.2** | 0.04 |
| | 5 | 800,115 | 2,196,890 | 603 | 8,453.5 | 100* | 53.613 | **8,445.3** | 0.10 |
| surgical | 1 | 115,732 | 302,936 | 600 | **5,594.5** | 1.70* | 1.859 | 5,618.7 | -0.43 |
| | 2 | 221,242 | 595,650 | 600 | **5,609.3** | 7.30* | 6.177 | 5,617.7 | -0.15 |
| | 5 | 537,772 | 1,473,792 | 602 | 5,622.1 | 100* | 39.406 | **5,612.6** | 0.17 |

carte. The marginal improvement potential of this solution is lower than in the case of PW minimization because of the cognitive costs associated with confirming defaulted-ON items paired with the workload of assigning the patient to the order set.

### 5.3 *A Platform for Order Set Optimization*

We extended the Java-based order set optimization platform from Gartner et al. (2017) to better communicate the effectiveness of the approaches to hospital practitioners. The difference now is that we have time-independent order sets and can choose between different clinical conditions. Figure 6 shows the platform.

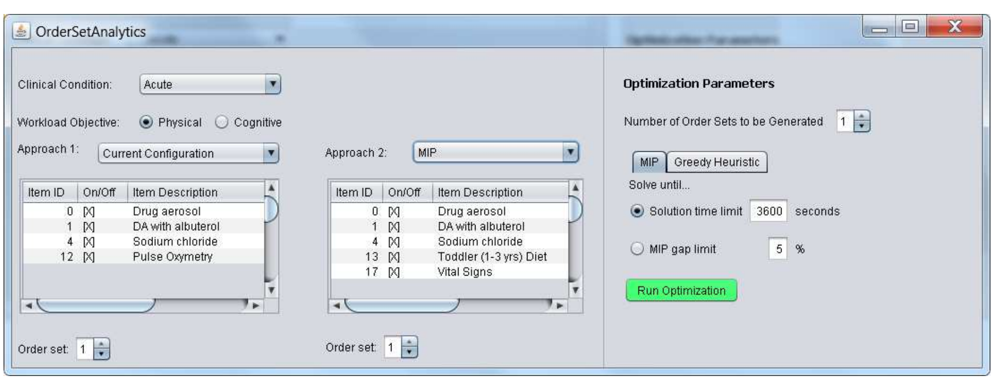


FIG. 6: Order set optimization platform

### 5.4 *Generalizability of the Approaches*

Our results have demonstrated that mathematical programming and the Greedy heuristic can reduce physical and cognitive workload for the prescription of order items. We argue that our approaches can be generalized to similar order set optimization problems in other developed-world countries, such as the U.K. national healthcare system (NHS). In this system, Fleming et al. (2009) evaluated clinical outcomes of order sets on mortality and costs. Our study setting is also applicable in the U.K. because patients' conditions can be selected based on Diagnosis-related groups (DRGs). These are named Healthcare Resource Groups (HRGs) in the NHS and are structured in a similar way.

In the model we tested the scenario what happened if the doctors would have been faced with the new order sets (based on demand). This assumes that the future patient population has a similar structure as compared to the one we used for testing the approaches.

## 6. Summary and Conclusions

In this paper, we have introduced a MIP and a Greedy-based global order set optimization approach to better design Hospital Information Systems. Depending on the number of allowed order sets and the solution time limit, our Greedy approach can outperform the MIP. Developing further heuristic optimization approaches as well as parametric optimization of the objective function coefficients are promising future directions for this research. Another area of future research is the development of upper and lower bounds for the problem as well as providing complexity results for arbitrary combinations of numbers of order sets, patients and objective function coefficients. Furthermore, the model could be extended towards incorporating precedence relations in the order items which relates to clinical pathway mining.

## A. Experiments for incrementing $K$

To benchmark the Greedy approach with optimal solutions, we selected a subset of 10 patients and performed the computation. The results for the PW and CW metric are shown in Table 7 and 8, respectively.

The figures from the PW metric reveal that the objective function value of the MIP decreases monotonically with increasing $K$. Another observation is that the computation times increase dramatically with increasing $K$. The figures also show that the gap between the heuristic's and the MIP's objective function value increases with increasing $K$. However, the gap is relatively small in the case where $K = 1$.

Table 7: Computation time analysis results for small test instances and the PW metric solved to optimality

| Condition | $\lvert\mathscr{K}\rvert$ | MIP #Var. | MIP #Constr. | MIP Comp. time [s] | MIP $z$ | MIP Optimality Gap [%] | Greedy Heuristic Comp. time [s] | Greedy Heuristic $z$ | Greedy Heuristic Heuristic Gap. [%] |
|---|---|---|---|---|---|---|---|---|---|
| acute | 1 | 4,007 | 7,538 | 2.3 | 401 | 0.0 | 0.012 | 406 | 1.25 |
| | 2 | 6,926 | 13,988 | 15.9 | 326 | 0.0 | 0.051 | 378 | 15.95 |
| | 3 | 9,845 | 20,438 | 100.4 | 268 | 0.0 | 0.044 | 330 | 23.13 |
| | 4 | 12,764 | 26,888 | 669.9 | 215 | 0.0 | 0.061 | 309 | 43.72 |
| | 5 | 15,683 | 33,338 | 876.7 | 169 | 0.0 | 0.085 | 315 | 86.39 |
| chronic | 1 | 4,834 | 8,452 | 0.7 | 469 | 0.0 | 0.009 | 469 | 0.00 |
| | 2 | 8,146 | 15,382 | 23.7 | 373 | 0.0 | 0.040 | 429 | 15.01 |
| | 3 | 11,458 | 22,312 | 172.4 | 296 | 0.0 | 0.097 | 373 | 26.01 |
| | 4 | 14,770 | 29,242 | 643.9 | 239 | 0.0 | 0.099 | 345 | 44.35 |
| | 5 | 18,082 | 36,172 | 1,626.2 | 186 | 0.0 | 0.106 | 376 | 102.15 |
| surgical | 1 | 4,523 | 8,290 | 0.7 | 445 | 0.0 | 0.010 | 447 | 0.45 |
| | 2 | 7,746 | 15,280 | 12.1 | 340 | 0.0 | 0.033 | 373 | 9.71 |
| | 3 | 10,969 | 22,270 | 112.2 | 291 | 0.0 | 0.067 | 328 | 12.71 |
| | 4 | 14,192 | 29,260 | 772.1 | 244 | 0.0 | 0.078 | 341 | 39.75 |
| | 5 | 17,415 | 36,250 | 1,386.1 | 200 | 0.0 | 0.104 | 356 | 78.00 |

The results from the CW optimization confirm the pattern that the objective function values decrease with increasing $K$. However, the gap between the heuristic's and optimal objective function value are increasing less dramatically.

Table 8: Computation time analysis results for small test instances and the CW metric solved to optimality

| | | MIP | | | | | Greedy Heuristic | | |
|---|---|---|---|---|---|---|---|---|---|
| Condition | $\lvert\mathscr{K}\rvert$ | #Var. | #Constr. | Comp. time [s] | $z$ | Optimality Gap [%] | Comp. time [s] | $z$ | Heuristic Gap. [%] |
| acute | 1 | 6,372 | 13,659 | 1.1 | 591.6 | 0.0 | 0.042 | 598.4 | 1.16 |
| | 2 | 11,656 | 26,230 | 13.4 | 585.9 | 0.0 | 0.196 | 598.4 | 2.13 |
| | 3 | 16,940 | 38,801 | 48.0 | 580.3 | 0.0 | 0.337 | 595.4 | 2.60 |
| | 4 | 22,224 | 51,372 | 52.1 | 575.4 | 0.0 | 0.314 | 598.4 | 4.00 |
| | 5 | 27,508 | 63,943 | 77.7 | 570.6 | 0.0 | 0.417 | 598.4 | 4.87 |
| chronic | 1 | 7,375 | 14,852 | 1.9 | 824.7 | 0.0 | 0.038 | 837.1 | 1.50 |
| | 2 | 13,228 | 28,182 | 38.6 | 815.9 | 0.0 | 0.200 | 837.1 | 2.60 |
| | 3 | 19,081 | 41,512 | 270.3 | 808.2 | 0.0 | 0.361 | 835.8 | 3.41 |
| | 4 | 24,934 | 54,842 | 736.9 | 801.1 | 0.0 | 0.377 | 837.1 | 4.49 |
| | 5 | 30,787 | 68,172 | 520.9 | 795.2 | 0.0 | 0.494 | 837.1 | 5.27 |
| surgical | 1 | 7,086 | 14,863 | 2.4 | 707.2 | 0.0 | 0.047 | 715.0 | 1.10 |
| | 2 | 12,872 | 28,426 | 15.3 | 699.5 | 0.0 | 0.184 | 714.9 | 2.20 |
| | 3 | 18,658 | 41,989 | 55.9 | 691.9 | 0.0 | 0.277 | 712.9 | 3.04 |
| | 4 | 24,444 | 55,552 | 347.7 | 686.2 | 0.0 | 0.397 | 713.4 | 3.96 |
| | 5 | 30,230 | 69,115 | 147.8 | 681.2 | 0.0 | 0.428 | 715.0 | 4.96 |

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